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Abstract

We use the Aguion and Howitt (2009) theoretical model of endogenous economic growth to explain the declining economic growth in developed economies in the period 1981-2009. Aguion and Howitt theoretical framework combines Solowian and Schumpeterian elements in a single scenario, so that labor-augmenting technological progress and capital accumulation per efficiency unit of labor are both caused not only by exogenous changes in the investment rate but also by shocks to the degree of efficiency in the Research and Development (R&D) expenditure process. Empirical results revealed that per worker output growth rates and capital stock per efficiency unit of labor growth rates both have a common panel unit root. Since the panel cointegration tests and estimates revealed a statistical significant negative long-run relationship between per worker output growth rate and capital stock per efficiency unit of labor, the interpretation of the econometric results analyzed from the Aguion and Howitt's theoretical perspective is that labor-augmenting technological progress is endogenously falling over time mainly because of an exogenous deterioration of the environment conditions for the transformation of the investment rate and R&D expenditures in technological progress.

JEL classification: O11, O31, O33, O41, O47, O57.

Keywords: Economic growth, Solowian and Schumpeterian models of growth, investment rate, R&D expenditures, capital stock per efficient unit of labor.

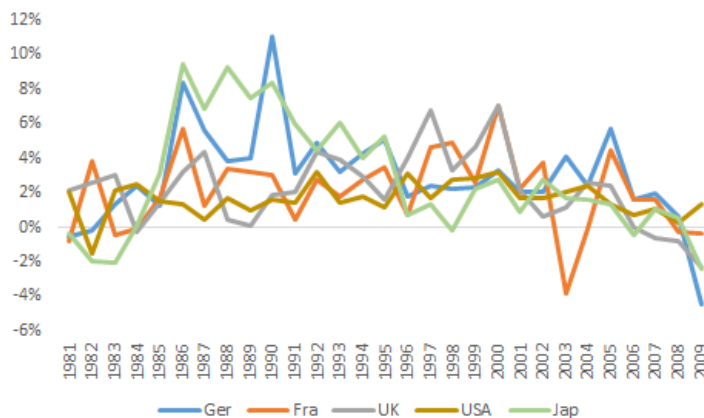
1. Introduction

Economists have noted a progressive and generalized decrease in annual growth rates of output per worker in the advanced economies since 1980s. Although developed economies have experienced serious difficulties in recovering their previous growth numbers since the 2008 crisis, recent literature has emphasized that these challenges are not only a cyclical issue related to the deep recent recession, but also a result of a progressive deterioration of long-run fundamentals of economic growth. To see this, figure 1 employs Penn World Tables version 8.1 data (Feenstra, R., Inklaar, R., and Timmer, M., 2015) in showing the time trajectories of annual per hour worked output growth rates between 1981 and 2009, for five advanced economies. It can be noted a clearly negative trend in economic growth rates, which is more pronounced in years 2008 and 2009.

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Figure 1: Per worker GDP annual growth rates



Source: Penn World Tables version 8.1 and authors calculations.

In particular, an IMF (2015) recent report documents that advanced economies have experienced a secular decline in GDP growth and average labor productivity growth since 1970s, and argues that these decreasing trend had been magnified by the 2008 crisis. Specifically, IMF showed that trend growth in output per hour worked declined from about 3 percent in 1970 to less than 1.5 percent in 2007. The recent literature has named this long-run slowdown in per worker product growth in advanced economies as “secular stagnation” (Summers, 2014; Gordon, 2015), which in part has been related by the literature to a long-run slowdown in Total Factor Productivity (TFP) growth.

We use the Aguion and Howitt (2009) theoretical model of endogenous economic growth and panel cointegration methods to explain the declining economic growth in developed economies in the period 1981-2009. Aguion and Howitt theoretical framework combines Solowian and Schumpeterian elements in a single scenario, so that labor-augmenting technological progress, which is the only factor that explains economic growth in the long-run, and capital accumulation per efficiency unit of labor, are both caused not only by exogenous changes in the investment rate, but also by shocks to the degree of efficiency in the Research and Development (R&D) expenditure process.

Results from panel unit root tests revealed that per worker output growth rates and capital stock per efficiency unit of labor growth rates both have a common unit root, which allowed us to test for panel cointegration. Since the panel cointegration tests and estimates revealed a statistical significant negative long-run relationship between per worker output growth rate and capital stock per efficiency unit of labor, the theoretical model suggests that declining investment rates contributes to the slowdown in economic growth, but they are not the principal explanation for declining per worker growth. The main interpretation of the econometric results analyzed from the Aguion and Howitt’s theoretical perspective is that labor-augmenting technological progress is endogenously falling over time, which is mainly motivated by an exogenous deterioration of the environment conditions for the transformation of investment and R&D expenditures in new technology. This result means that marginal productivity of capital stock for making innovations has decreased. Although investment rates and efficiency of R&D expenses both explain the decelerating growth rates, theoretical interpretation of econometric results suggests that the second exogenous force domain over the first one.

Declining investment rates and decreasing efficiency of R&D investments explaining low growth rates is consistent with various findings in the literature. For instance, Desroches and Francis (2006) and Eichengreen (2015) argue that the slowdown in productivity growth has been related to a decrease in

real interest rates since 1980s, which can be explained by an excess of desired savings over desired investments (Fisher, 2006; IMF, 2014; Eichengreen, 2015). Furthermore, Eichengreen (2015) point that low real interest rates and the slow economic growth could be associated to a dearth in attractive investment opportunities. For instance, Gordon (2012) argues that returns to innovation processes have slowed since 1970s.

The structure of the paper is as follows. Section 2 describes the theoretical model of Aghion and Howitt (2009) to explain the decelerating per worker output growth rates. Section 3 exposes data sources and the econometric strategy, followed by section 4 where results are documented and summarized. Finally, section 5 presents the interpretation of econometric results based on the Aguión and Howitt endogenous growth model, and the conclusions.

2. Theoretical framework

In this section we expose the Aguión and Howitt endogenous growth hybrid model as our reference theoretical framework¹. Firstly, we explain why this model is suitable in studying the slowdown in per worker output growth rates of developed economies. Later on, we show the assumptions and workings of the model for determining the optimal endogenous long-run economic growth and capital stock per efficiency unit of labor. These elements will be useful in understanding the empirical strategy and the results from the econometric estimates.

2.1. Endogenous growth model approach

It is common to conclude from documented growth accounting exercises that capital deepening explains an increasing part of economic growth. Using data from Penn World Tables (Heston, Summers, and Aten, 2002) Aguión and Howitt (2009) find that TFP growth share on economic growth was 68% in the period 1960-2000, whereas physical capital deepening share was 32% during that period. Jorgenson (1995) makes a more exhausting growth accounting exercise in including human capital as a factor that contributes to economic growth. Under these conditions, capital deepening (physical and human capital) contributes to around 70% of economic growth, making less the TFP growth share (30%) because solow residual turns smaller once physical and human capital growth has been subtracted from per worker income growth. This result is consistent with that found by Mankiw, Romer and Weil (1992), who suggested that capital growth share on national income is about two-thirds.

As remarked by Aguión and Howitt, the accountant discussion around the role of capital and TFP growth on per worker output growth has been sustained by Young (1995) and Hsieh (2002). Estimating the TFP growth as a solow residual, Young finds that Singapore, Hong-Kong, Taiwan and Korea reached most of their remarkable income growth rates through capital accumulation and a greater efficiency in allocating productive resources, instead of technological progress. However, Hsieh argues that capital stock is usually overestimated, and further he uses the “dual method”² for estimating the TFP growth, finding that total factor technological progress played a more important role in generating per worker income growth.

Nevertheless, even when capital stock growth accounts between 30% and 70% of per worker output growth, all long-run economic growth is entirely caused by technological progress, which is consistent with the Solow growth model. As Aghion and Howitt explain, an accounting relationship is not the same thing as a causal relationship. To see this, consider the following labor-augmenting technology production function with constant returns to scale:

¹Aghion and Howitt (2009), Chapter 5.

²See Aghion and Howitt (2009) for a more detailed description of the “dual method”.

$$Y = A^{1-\alpha} L^{1-\alpha} K^\alpha$$

Where Y is the aggregate level of output, K is aggregate capital stock, L is labor input and A is the labor-augmenting technology, which captures the productivity of capital.

In the equation above, it can be noted that $B = A^{1-\alpha}$ is the Total Factor Productivity (TFP) parameter. Dividing the last equation by L , output per worker becomes:

$$\frac{Y}{L} = y = B \left(\frac{K}{L} \right)^\alpha = Bk^\alpha$$

Expressing the last equation in terms of growth rates of the variables, per worker output growth rate takes the form:

$$\frac{\dot{y}}{y} = g = \frac{\dot{B}}{B} + \alpha \frac{\dot{k}}{k} \quad (1)$$

This equation says that economic growth is the sum of the rate of TFP growth and the “capital deepening” process ($\alpha \frac{\dot{k}}{k}$). Equation (1) implies that:

$$\frac{\dot{B}}{B} = (1 - \alpha) \frac{\dot{A}}{A}$$

Following the Solow growth model, per worker output growth rate is equal to the labor-augmenting technological process:

$$\frac{\dot{A}}{A} = \frac{\dot{y}}{y} \quad (2)$$

And this implies that TFP growth is $(1 - \alpha)\%$ of long-run per worker output growth:

$$\frac{\dot{B}}{B} = (1 - \alpha) \frac{\dot{y}}{y} \quad (3)$$

Equation (2) says that labor-augmenting technological progress is entirely the cause of long-run economic growth, and equation (3) says that TFP growth is a fraction $(1 - \alpha)$ of per worker growth.

As Aghion and Howitt explain, the term $\alpha \frac{\dot{k}}{k}$ is the economic growth rate that would have been observed if the capital-labor ratio had grown at its observed rate, but there had been no technological progress. However, it is hard to observe a significant increase in capital-labor ratio with a constant state of technological progress, because in general one can see that a raise in capital stock is accompanied by improves in the quality of the new capital goods³, but this quality adjustment is imperfectly observable. As the growth model implies that technological progress is required for

³As argued by Aghion and Howitt (2009), the strong fall of capital goods relative prices documented by Gordon (1990) has an explanation. In many cases these falls did not happen because the same amount of capital goods can be produced using a less quantity of production factors, but because higher quality of capital goods can be produced in the current time, so the price of a quality adjusted capital good must fall. For example, even when the cost of producing a computer today is similar than 10 years ago, people today can buy a much better machine for the same price.

avoiding diminishing returns from raising the capital-labor ratio, technological progress is the principal cause of both components of per worker growth, i. e. capital deepening and TFP growth rates.

The Solow growth model considers that investment rate, depreciation rate and population growth rate are exogenous factors that affect long-run per worker output. However, since long-run growth is exogenously explained by technological progress, then there are no elements that explain endogenously technological progress, and its interactions with capital accumulation. Therefore, it does not capture the fact that increases in capital stock are probably accompanied by an improvement in the included quality standards. As a starting solution, the interaction between higher quality of intermediate goods and economic growth is modeled by the Schumpeterian growth model (Aghion and Howitt, 1992), making endogenous the technological progress through the existence of private R&D expenditures and a probability of success in the innovation process, where if innovation process succeeds, then positive long-run per worker income growth will take place. Since the Solow model is consistent with growth accounting results but it keeps the idea that all long-run growth is caused by technological progress, it seems reasonable that a mixture between Neoclassical (Solowian) and Schumpeterian elements may be adequate for explaining endogenously long-run economic growth.

2.2. The model

The key purpose of this work is to explain the long-lasting decrease in the long-run growth rate of per worker output for developed economies. The endogenous growth model developed by Aguion and Howitt (2009) is employed as the reference theoretical framework. This model, called the hybrid model, combines Solowian and Schumpeterian elements in a single scenario, so labor-augmented technological progress, which is the only factor that explains economic growth in the long-run, and capital accumulation, are both caused not only by exogenous changes in the investment rate, but also by shocks to the degree of efficiency in the Research and Development (R&D) expenditure process.

Compared to the Solow model, Aguion and Howitt (2009) show that the hybrid model offers an improved explanation of the growth accounting results for advanced economies, so that Total Factor Productivity (TFP) growth and capital deepening shares are now caused endogenously by the investment rate and innovation trajectories, which in turn account for long-run per worker income growth.

The model considers three kinds of goods: i) a final good, ii) labor, and iii) a continuum of specialized intermediate goods. The final good is storable in form of capital stock, and it is assumed that intermediate goods are produced employing capital stock. There are L workers, each of them supplies inelastically one unit of skilled work. The final good is produced in a perfectly competitive market, with an aggregate constant returns to scale production function:

$$Y_t = L^{1-\alpha} \int_0^1 A_{it}^{1-\alpha} x_{it}^\alpha di; \quad 0 < \alpha < 1 \quad (4)$$

Where A_{it} is the number of efficiency units of labor and the productivity of the intermediate input in sector i , x_{it} is the flow of the intermediate input from sector i , and L is the aggregate labor input. For simplicity, it is assumed that $L = 1$.

Intermediate inputs are produced by monopolist entrepreneurs, through the production function:

$$x_{it} = K_{it} \quad (5)$$

Where K_{it} is the capital stock used as a production factor in generating intermediate products. Given that final goods are produced under perfect competition, but intermediate products are generated

under monopolistic competition, it is assumed that the price of intermediate inputs equals marginal productivity of intermediate inputs:

$$p_{it} = \frac{\partial Y_t}{\partial x_{it}} = \alpha A_{it}^{1-\alpha} x_{it}^{\alpha-1}$$

The equation above represents the demand function of intermediate input for final good firms, whereas it depicts the inverse demand function dealt by the monopolist. So the cost of producing x_{it} for the local monopolist is:

$$r_t x_{it} = r_t K_{it}$$

Then the local monopolist's profits are:

$$\Pi_{it} = p_{it} x_{it} - r_t x_{it} = \alpha A_{it}^{1-\alpha} x_{it}^\alpha - r_t x_{it} \quad (6)$$

Where r_t is the rental rate of capital stock. The local monopolist chooses x_{it} to maximize its profits, such that:

$$\frac{\partial \Pi_{it}}{\partial x_{it}} = \alpha^2 A_{it}^{1-\alpha} x_{it}^{\alpha-1} - r_t = 0 \quad \rightarrow \quad x_{it} = A_{it} \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} \quad (7)$$

The rental rate of capital is determined by the supply and demand for capital stock. In particular, capital supply is historically predetermined, whereas aggregate demand for capital can be expressed as:

$$\int_0^1 K_{it} = \int_0^1 x_{it}$$

The equilibrium condition above can be rewritten as the endogenous aggregate capital stock:

$$K_t = \int_0^1 \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} A_{it} di = \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} A_t \quad (8)$$

Where $\int_0^1 A_{it} di$ is the aggregate capital productivity parameter. Let $\tilde{k} = \frac{K}{AL} = \frac{K}{A}$ the capital stock per efficient work unit, so equation (8) can be written in the form:

$$\tilde{k} = \left(\frac{\alpha^2}{r_t} \right)^{\frac{1}{1-\alpha}} \quad \rightarrow \quad r_t = \alpha^2 \tilde{k}_t^{\alpha-1} \quad (9)$$

Equation (9) says that the rental rate of capital is negatively related to the capital stock per efficient work unit. From equations (7) and (8) it can be inferred that:

$$x_{it} = A_{it} \left(\frac{K_t}{A_t} \right) = A_{it} \tilde{k} \quad (10)$$

Substituting equations (9) and (10) in (6), local monopolist profits function becomes:

$$\Pi_{it} = \alpha A_{it} \tilde{k}_t^\alpha - (\alpha^2 \tilde{k}_t^{\alpha-1}) A_{it} \tilde{k} = \alpha(1 - \alpha) \tilde{k}_t^\alpha A_{it}$$

$$\rightarrow \Pi_{it} = \tilde{\pi}(\tilde{k}_t) A_{it}; \quad \tilde{\pi}(\tilde{k}_t) = \alpha(1 - \alpha) \tilde{k}_t^\alpha \quad (11)$$

It can be noted from equation (11) that monopolist i profit function is increasing in \tilde{k}_t , and the reason is that a greater level of capital stock per efficiency unit of labor reduces per unit costs of production, r_t . Substituting equation (10) in (4), aggregate production function is reexpressed as:

$$Y_t = \int_0^1 A_{it}^{1-\alpha} A_{it}^\alpha \tilde{k}_t^\alpha = A_t \tilde{k}_t^\alpha \quad (12)$$

2.3. Innovation and economic growth

It is assumed that each period t an entrepreneur of sector i spends resources in R&D activities with a certain probability of innovate successfully. If the entrepreneur is successful, then it becomes the next period local monopolist because the innovation will create an improved more productive version of the intermediate product, and no other entrepreneur can produce it. If the entrepreneur fails, no innovation process will be available so intermediate input will not improve its quality. In this case, the monopoly will pass to another entrepreneur chosen at random who is able to produce old intermediate products. Specifically the probability of success in R&D expenditures is expressed as:

$$\mu_t = \phi(\eta_t)$$

Where $\eta_t = \frac{R_{it}}{A_{it}^*}$ is the productivity-adjusted level research, R_{it} are expenditures in research activities, and A_{it}^* is the productivity of the intermediate product. If the entrepreneur succeeds, then $A_{it}^* = \gamma A_{it-1}$ ($\gamma > 1$) will be the productivity of the new improved intermediate product. However, if the entrepreneur fails then $A_{it}^* = A_{it} = A_{it-1}$ and the intermediate input used in t will be the same as in $t - 1$. The assumption of A_{it}^* being inversely related to the probability of success, μ_t , is because it is more difficult to innovate as technological progress increases over time. Therefore, what matters in augmenting the probability of success is the productivity-adjusted level of research, $\eta_t = \frac{R_{it}}{A_{it}^*}$. The probability of success μ_t follows a Cobb-Douglas form:

$$\mu_t = \lambda \eta_t^\sigma; \quad \lambda > 0; \quad 0 < \sigma < 1$$

Where λ is the efficiency of research. Hence the profits function if the entrepreneur succeeds is:

$$\phi\left(\frac{R_{it}}{A_{it}^*}\right) \Pi_{it}^* - R_{it}$$

The entrepreneur will choose R_{it} so that it maximizes its profits:

$$\begin{aligned} \frac{\partial \left[\phi\left(\frac{R_{it}}{A_{it}^*}\right) \Pi_{it}^* - R_{it} \right]}{\partial R_{it}} &= \phi' \left(\frac{R_{it}}{A_{it}^*} \right) \Pi_{it}^* \left(\frac{1}{A_{it}^*} \right) - 1 = 0 \\ \rightarrow \phi' \left(\frac{R_{it}}{A_{it}^*} \right) \Pi_{it}^* \left(\frac{1}{A_{it}^*} \right) &= 1 \end{aligned}$$

By equation (11) it can be assumed that:

$$\frac{\Pi_{it}^*}{A_{it}^*} = \frac{\Pi_{it}}{A_{it}} = \tilde{\pi}(\tilde{k}_t)$$

In this case entrepreneur's first order condition becomes:

$$\phi'(\eta_t)\tilde{\pi}(\tilde{k}_t) = 1 \quad (13)$$

Equation (13) is called the research arbitrage condition. This optimality condition says that marginal benefits of spending in R&D (left hand side) must be equal to its marginal cost (right hand side). So an increase in the capital stock per efficient work unit will diminish per unit costs, r_t , and then profits will raise. Given that $\phi'(\eta_t)$ is decreasing in η_t , satisfying the arbitrage condition implies that η_t must boost in order to maximize profits. This means that augmenting \tilde{k}_t makes more profitable to increase expenditures in technology-adjusted research, which in turn raises the probability of success in the innovation process. This can be seen by solving equation (13) for η_t and μ_t :

$$\eta_t = \left[\sigma \lambda \tilde{\pi}(\tilde{k}_t) \right]^{\frac{1}{1-\sigma}}$$

$$\mu_t = \lambda \left[\sigma \lambda \tilde{\pi}(\tilde{k}_t) \right]^{\frac{\sigma}{1-\sigma}}$$

As in the Schumpeterian model, the productivity growth rate g_t is the frequency of innovations μ_t times the factor $(\gamma - 1)$:

$$g_t = (\gamma - 1) \lambda \left[\sigma \lambda \tilde{\pi}(\tilde{k}_t) \right]^{\frac{\sigma}{1-\sigma}} \quad (14)$$

Which means that:

$$g_t = \tilde{g}(\tilde{k}_t); \quad \tilde{g}' > 0$$

2.4. Capital accumulation and economic growth: the steady state

As usual in the Solow growth model, suppose a neoclassical labor-augmenting technology production function, adjusted by efficient units of work:

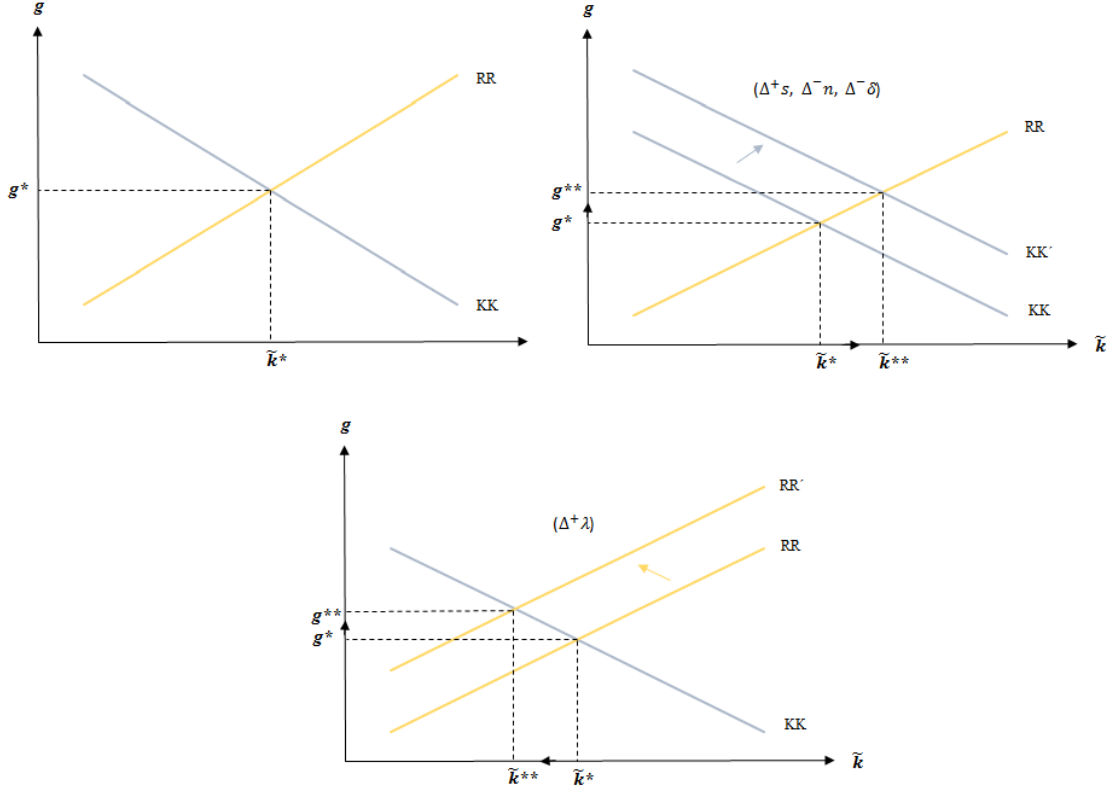
$$\tilde{y}_t = \tilde{k}_t^\alpha$$

Where \tilde{y}_t is output per efficiency unit of labor. A steady state condition in the Solow model is that savings are equal to the depreciation of the capital stock, so that:

$$\dot{\tilde{k}}_t = 0 \quad \leftrightarrow \quad s\tilde{y} = (\delta + g + n)\tilde{k}$$

Where $\dot{\tilde{k}}_t$ is the derivative of capital stock per efficiency unit of labor with respect time, s is the saving (investment) rate, δ is the depreciation rate and n is the population/labor growth rate. Substituting $\tilde{y} = \tilde{k}^\alpha$ in the equation above and solving for \tilde{k} :

Figure 2: Long-run equilibrium patterns in the Aghion-Howitt model



Source: Aghion and Howitt (2009).

$$\tilde{k} = \left(\frac{s}{\delta + g + n} \right)^{\frac{1}{1-\alpha}} \quad (15)$$

As in the Solow model, in steady state capital stock per efficiency unit of labor is negatively related to per worker output growth. Furthermore, since in steady state $\dot{\tilde{k}}_t = \dot{\tilde{y}}_t = 0$, then per worker income growth will be equal to the labor-augmenting technological progress, such that: $\frac{\dot{\tilde{y}}}{\tilde{y}} = \frac{\dot{A}}{A} = g$.

Therefore, the reduced form of the model around the steady state is represented by equations (14) and (15), which are called respectively the “research” and “Solowian” equations. As it is shown by Aghion and Howitt (2009), these two equations can be drawn respectively in a two dimensional plane as the “RR” and “KK” curves, just as it is in figure 2. As mentioned above, the research equation implies that economic growth is increasing in \tilde{k} because when capital per efficiency unit of labor raises then incentives to innovate increase, which in turn boosts productivity and economic growth. In contrast, the Solowian curve says that long-run economic growth is a decreasing function of \tilde{k} because of the assumption of decreasing marginal returns from capital stock per efficiency unit of labor, implied by the Solow model. As in the neoclassical framework, the steady state equilibrium between g and \tilde{k} is dynamically stable⁴.

As a result, changing key parameters in both equations allows making steady state comparative static exercises. In particular, an increase in efficiency of research λ will shift RR curve up. As a result,

⁴See Aghion and Howitt (2009) chapter 5 annex for details.

long-run economic growth will raise and capital stock per efficiency unit of labor will turn down. This result means that if efficiency of research improves, then frequency of innovations increases, making possible a greater long-run per worker income growth, which causes less capital stock per efficiency unit of labor, given the workings of the decreasing marginal returns implied by the neoclassical equation. In contrast, an investment rate hike pushes up and right the curve derived from equation (15), which generates both an increase in long-run economic growth and per capital stock efficiency unit of labor. The reason is that a greater level of \tilde{k} makes more profitable to increase the research efforts by monopolists, which in turn raises frequency of innovations, and therefore economic growth.

3. Data and empirical strategy

In the section above it was shown that the theoretical model implies that long-run economic growth and capital stock per efficiency unit of labor were functions of certain exogenous components. In particular, reduced form equations for g and \tilde{k} makes that long-run movements of these two variables endogenously depend of exogenous changes in λ , s , δ and n . In order to estimate these relations and to give an explanation to the persistent low per worker growth rates in advanced economies, we start by showing and analyzing the data. Later on, details of the econometric strategy will be explained.

3.1. Data

Data for obtaining the processes $\{g, \tilde{k}, s, \delta, n\}$ were collected from the Penn World Tables version 8.1. Our dataset covers the annual time period 1981-2009 and we considered 18 developed economies⁵. We use output-side real GDP ($rgdpo$) as our measure of real aggregate GDP variable. To calculate per worker real GDP, aggregate real output is divided by a measure of total hours worked by employed population. This measure is calculated as the average annual hours worked by an engaged person (avh), multiplied by the number of persons engaged in employment (emp):

$$(per\ worker\ real\ gdp)_t = y_t = \frac{rgdpo_t}{(avh_t)(emp_t)}$$

This measure of per worker output is suitable from a neoclassical point of view, because it can be understood as the real output produced per hour worked. Moreover, capital stock per efficiency unit of labor is calculated as the real value of capital stock (ck) divided by our measure of labor, $(avh_t)(emp_t)$, which is multiplied by a measure of labor-augmenting technological progress, which in turn is obtained as a Solow residual. Assuming a constant returns to scale production technology, we have:

$$\tilde{k}_t = \frac{ck_t}{A_t(avh_t)(emp_t)}$$

Where $A_t = \left\{ \frac{rgdpo_t}{(ck_t)^{1-\theta_t}[(avh_t)(emp_t)]^{\theta_t}} \right\}^{\frac{1}{\theta_t}}$ being θ_t the time-varying labor share in real aggregate output (labsh).

Measures for investment, depreciation and population growth rates are obtained from the Penn World Tables. Specifically, for the saving rate we chose the investment (gross capital formation) shares in real GDP (csh_i), and for depreciation and population growth rates we respectively took “average depreciation rate of the capital stock (δ)” and “population (n)”.

⁵The countries in the sample are: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Japan, Netherlands, Norway, Portugal, South Korea, Spain, Sweden, United Kingdom, United States.

3.2. Empirical strategy

As the reduced form of our theoretical framework consists in a stable long-run equilibrium relationship between per worker output growth g and capital stock per efficiency unit of labor \tilde{k} , we want to estimate empirically how this equilibrium endogenously changes when certain exogenous variables are shocked. In particular, it has shown above that Aguion and Howitt model implies that positive exogenous shocks to the investment rates (or negative shocks to depreciation and population growth rates) yield a long-run increase in both g and \tilde{k} . In contrast, we have seen that an exogenous rise in the efficiency of R&D investments rises frequency of innovations, which results in higher g accompanied by a decrease in \tilde{k} .

From an econometric point of view, it is hard to estimate how long-run equilibrium between g and \tilde{k} changes when one exogenous variable changes separately. Therefore, we propose estimating “continuous” endogenous changes in steady-state equilibrium $\{g^*, \tilde{k}^*\}$ by employing panel cointegration techniques. In particular, we want to estimate the last relation through testing for panel cointegration in the endogenous variables g_{it} and \tilde{k}_{it} ⁶ and by estimating the corresponding cointegrating vector. Given the predictions made by the theoretical model when there are shocks to the exogenous variables, one could expect that if the long-term relation between g and \tilde{k} is positive and stable, then exogenous changes in investment, depreciation and population growth rates would domain over exogenous changes in efficiency of R&D expenditures through time. In graphical terms, this could be seen as successive shifts of the Solowian (KK) curve along the Schumpeterian (RR) curve. Nevertheless, if the last relationship is negative and stable, hence exogenous shocks to efficiency of R&D expenses would domain over exogenous changes in investment, depreciation and population growth rates. Analogously, this could be seen as continuous shifts of the Schumpeterian (RR) curve along the Solowian (KK) curve. Since the dominance of Solowian exogenous movements over Schumpeterian exogenous shocks, or backwards, determines the long-term relationship between per worker growth and capital accumulation per efficient work unit, this link is entirely an empirical issue, and as such, there are reasons for expecting either a positive or a negative sign of the long-run coefficient that relates g_{it} and \tilde{k}_{it} .

In dealing with the existence and (if possible) estimates of panel cointegration between g and \tilde{k} , we start by reviewing the panel unit root tests, panel cointegration tests and panel cointegration estimation methods that we will use in the econometric exercise.

3.2.1. Panel unit root tests

Following Baum (2006) and Baltagi (2013), consider a panel data autorregressive model of the form:

$$y_{it} = \rho_i y_{it-1} + D_{it}' \theta_i + \varepsilon_{it} \quad (16)$$

Where $i=1,...,N$; $t=1,..., T$; ε_{it} is the white noise error term and D_{it} is a term which captures deterministic components. In this case, if $D_{it}' = 0$ then there will not be any deterministic component in (16); however if $D_{it}' = 1$ then it will control for panel-specific fixed effects; and if $D_{it}' = (1, t)$ the equation will have panel-specific constants and time trends. Analogously to the single time series case, most panel unit root tests consist in testing the null hypothesis of $H_0 : \rho_i = 1$ against the alternative of $H_1 : \rho_i < 1$. Equation (16) can be rewritten as:

$$\Delta y_{it} = \varphi_i y_{it-1} + D_{it}' \theta_i + \varepsilon_{it} \quad (17)$$

⁶In our specific sample N and T dimensions are defined by $i=1,..., 18$ and $t=1,..., 29$.

Where $\varphi_i = \rho_i - 1$. By this way, the panel unit root tests will have $H_0 : \varphi_i = 0$ against the alternative of $H_1 : \varphi_i < 0$. As in the familiar case of single time series, the null hypothesis is that y_{it} is a non-stationary process, while rejecting it will imply that y_{it} is stationary.

On the other hand, the panel unit root test developed by Hadri (2000) is a generalization of the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test used in time series, so the null hypothesis is that all panels y_{it} are stationary against the alternative that some panels are stationary.

We employ five panel unit root tests, which can be divided in three kinds of tests. The first kind are the tests developed by Levin, Li and Chu (LLC, 2002) and Breitung (2000) which restricts the autorregressive parameter in (17) to be the same for all panels, so that $\varphi_i = \varphi$. Another kind of tests that we consider are those that permit the autorregressive parameter to be panel-specific, such as Im, Pesaran and Shin (2003) and Fisher-Type tests. Finally, the third kind of test is that developed by Hadri (2000), which builds a residual-based LM test from an autorregressive panel process similar to (16). Common features shared by these tests are: i) they share the fact that all the test statistics are asymptotically distributed $N(0, 1)$, ii) their asymptotic convergence properties make behave them relatively well under $T > N^7$, and iii) they assume cross-sectional independence.

Specifically, the LLC test specifies an equation which is very similar to (17), with the difference that the test restricts the autorregressive term to be common across the panels and the test controls for serial correlation in the error term by considering lags to dependent variable, as in the augmented Dickey-Fuller test. So the model proposed by LLC is:

$$\Delta y_{it} = \varphi y_{it-1} + D'_{it}\theta_i + \sum_{k=1}^p \alpha_{ik} \Delta y_{it-k} + \mu_{it} \quad (18)$$

The lags in the dependent variable can be selected by information criteria such that serial correlation in μ_{it} terms vanish and they become panel-specific homoskedastic, further permitting their variance to differ across contemporaneous units. Given that the null hypothesis is that panels have unit roots and there exist fixed effects, the t-statistic follows a nonstandard distribution and the estimated value of φ will be biased towards zero. As noted by Baum (2006), LLC builds an adjusted-bias t-statistic, t^* , that is asymptotically distributed $N(0,1)$ under certain conditions. If there is no deterministic terms in (18) (not controlling for fixed effects nor trends) t^* will asymptotically distribute standard normal if $\sqrt{N}/T \rightarrow 0$, which implies that T will grow at a slower rate than N. However, once panel-specific constant terms and trends are specified, then t^* will asymptotically distribute standard normal if $N/T \rightarrow 0$, which implies that T must grow faster than N, which in turn means that N should be less than T (Baum, 2006; Baltagi, 2013).

For the Breitung test, supposed that the variable of interest forllow an AR(1) process, so that:

$$y_{it} = D'_{it}\theta_i + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \varepsilon_{it} \quad (19)$$

The test procedure makes vanish the serial correlation in the error terms, and it has two possible outcomes, depending on the assumption about the correlation across panels of the terms ε_{it} . In particular, if ε_{it} is uncorrelated across the N units then using the non-robust version of the test is suitable. On the contrary, if there exists cross-section correlation of ε_{it} therefore the test allows using a robust version so that this cross-correlation is controlled. As in equation (19) the null hypothesis is that y_{it} as a whole has a unit root, then $H_0 : \gamma_1 + \gamma_2 = 1$ against the alternative of y_{it} being a stationary process $H_1 : \gamma_1 + \gamma_2 < 1$. Independent wether the Breitung test is either used with or without time trend, then the non-robust and robust test-statistics, $\{\lambda, \lambda^{robust}\}$, are asymptotically distributed $N(0, 1)$ when $T \rightarrow \infty$ followed by $N \rightarrow \infty$, which in practical terms implies $T > N$.

⁷See Baltagui (2013) for a detailed discussion of the asymptotic properties of the panel unit root tests.

Moreover, Im, Pesaran and Shin (2003) test (IPS) is very similar to the LLC test, in the sense that IPS follows the same autorregressive structure of the model, with the difference that the autorregressive coefficient is panel-specific. As in the single time series case like Dickey-Fuller, the specification and estimation procedures change when serial correlation in the error terms is present. To see this, first consider the case in which there is no serial correlation along the T dimension, so that y_{it} follows a process of the form:

$$\Delta y_{it} = \varphi_i y_{it-1} + D_{it}' \theta_i + \mu_{it} \quad (20)$$

Where φ_i is the panel-specific autorregressive coefficient. They assume that μ_{it} is serially uncorrelated in both dimensions N and T and that is the reason why there is no lags of the dependent variable in the left hand side, but it allows for different variances across the panels. For hypothesis testing, φ_i is estimated for each i and then panel-specific t-statistics are computed, so that they are averaged to obtain a single t-statistic. The null hypothesis is that $H_0 : \varphi_i = 0$ for all i (all panels have unit roots) against the alternative $H_0 : \varphi_i < 0$, which implies that some panels are stationary. The test builds various test statistics, such as \bar{t} which is the average of all panel-specific t-statistics t_i ; \tilde{t} which is the average of similar t-statistics as \bar{t} but with the difference that \tilde{t}_i is constructed by a different error variance estimator of (20); and Z_t and $Z_{\tilde{t}}$ are respectively standarized versions of \bar{t} and \tilde{t} , although Z_t does not have an asymptotic normal distribution, which makes it not commongly appropriate for hypothesis testing (Baum, 2006). Hence, these three test statistics are computed with the objective of making three null hypothesis testing exercises through closely related statistics, which makes robust the result of the test. Using the test under serially uncorrelated error terms across T is suitable when N and T are fixed.

However, when there is serial correlation in μ_{it} , information-criterion based selected lags are added to equation (20) for removing autocorrelation. In this case IPS test considers the following model:

$$\Delta y_{it} = \varphi_i y_{it-1} + D_{it}' \theta_i + \sum_{k=1}^p \alpha_{ik} \Delta y_{it-k} + \mu_{it} \quad (21)$$

Under this situation a different built test statistic is generated, labeled $W_{\tilde{t}}$, which is appropriate when $T \rightarrow \infty$ followed by $N \rightarrow \infty$, meaning that it is required relatively large dimensions N and T .

Fisher-Type tests performs units root tests for each panel, and then makes transformations to the p-values according to the four methos developed by Choi (2001). The panel-specific unit root test must be chosen either to be Augmented Dickey-Fuller or Phillips-Perron tests. Each one of these transformation methods has its own test statistic and p-values, which are labeled inverse chi-squared (P), inverse-normal (Z), inverse-logit (L) and modified inverse chi-squared (Pm). Null-hypothesis is that all panels have unit roots against the alternative that at least one panel is stationary. Using this test is appropriate when $T \rightarrow \infty$ and N could be either finite or infinite.

Finally, we use the panel unit root test developed by Hadri (2000), which is considered a residual-based LM test. Opposed to the last four tests, in Hadri panel unit root test the null hypothesis is that all panels are stationary, but the alternative is that at least one panel has unit root, analogous to the time series KPSS test. Consider the following process for y_{it} with (optional) time trend:

$$y_{it} = z_{it} + \alpha_i t + \varepsilon_{it} \quad (22)$$

Where $z_{it} = z_{it-1} + u_{it}$ is a random walk process, and ε_{it} and u_{it} are mutually independent normal variables that are independent and identically distributed across i and t . Using back substitution of equation (22):

$$y_{it} = z_{i0} + \alpha_i t + \sum_{s=1}^t u_{is} + \varepsilon_{it} = z_{i0} + \alpha_i t + v_{it} \quad (23)$$

Where $v_{it} = \sum_{s=1}^t u_{is} + \varepsilon_{it}$. Then the null hypothesis is $H_0 : \lambda = \frac{\sigma_y^2}{\sigma_\varepsilon^2}$ against the alternative $H_0 : \lambda > 0$. If the null hypothesis is not rejected, then $v_{it} = \varepsilon_{it}$ and the variable y_{it} is stationary in all panels. The test calculations has the option of making a variant of the test robust to heteroskedasticity across panels, and also has the option of building the test robust to serial correlation and heteroskedasticity. Using the test is suitable when $T \rightarrow \infty$ followed by $N \rightarrow \infty$, which in practical terms implies a large T and a moderate N (Baum, 2006; Baltagi, 2013).

3.2.2. Panel cointegration tests

Following Baltagi (2013), consider a panel regression of y_{it} against x_{it} of the form:

$$y_{it} = \alpha_i + x_{it}'\beta + e_{it} \quad (24)$$

Where y_{it} and x_{it} are non-stationary variables and α_i controls for non-observed heterogeneity in each panel. As in the Engel and Granger (1987) methodology for time series, Pedroni (1999, 2004) and Kao (1999) construct residual-based tests which consist in evaluating whether the term e_{it} is a stationary process in a panel data framework, such that the absolute value of the autorregressive coefficient in $e_{it} = \rho e_{it-1} + v_{it}$ (if there is no serial correlation) or in $e_{it} = \rho e_{it-1} + \sum_{s=1}^{p_i} \theta_{is} \Delta e_{it-s} + v_{it}$ (if there is serial correlation) takes a value less than unity.

In particular, Pedroni (1999, 2004) developed eleven statistics for testing panel cointegration, and each test statistic differ in size and power, depending on the N and T dimensions⁸. The first eight test statistics test for cointegration when ρ is restricted to be same across panels (within dimension) and the remaining three tests allow ρ to differ across panels (between dimension), and therefore there is a specific ρ_i for each cross-section. For hypothesis testing, the null hypothesis of no-cointegration is $H_0 : \rho_i = 1$, while alternative hypothesis under the within-dimension case ($\rho_i = \rho$) is $H_a : \rho < 1$ and under the between-dimension case the alternative becomes $H_a : \rho_i < 1$ for all i . Finally, all test statistics converge approximately to a standard normal distribution $N(0, 1)$.

Moreover, the structure of Kao (1999) panel cointegration test is similar to Pedroni test. Remarkable differences are that Kao test assumes no time trends (but heterogeneous constant terms) and constrains the residual equation to have a common autorregressive parameter accompanying the residual lagged term. Specifically, assume that the residuals in (24) can follow one of the following processes:

$$e_{it} = \rho e_{it-1} + v_{it} \quad (25)$$

$$e_{it} = \rho e_{it-1} + \sum_{s=1}^{p_i} \theta_{is} \Delta e_{it-s} + v_{it} \quad (26)$$

When estimating the model, one can assume that there is no serial correlation in error terms (as indicated in equation (25)), in which case Kao developed the test based on Dickey-Fuller (DF) regressions. Further, when the existence of serial correlation is assumed (as indicated in equation (26)), then the test works based on Augmented Dickey-Fuller regressions (ADF). Similar to Pedroni

⁸See Baltagi (2013) for details involved in the calculations of Pedroni's test statistics.

test, in Kao the null hypothesis of panel cointegration is $H_0 : \rho = 1$ against the alternative $H_a : \rho < 1$. All Kao test statistics are asymptotically distributed $N(0, 1)$.

Unlike the above tests based on the Engle-Granger methodology, the Fisher-type test combines panel-specific Johansen tests for building a whole-panel combined test, which was developed by Maddala and Wu (1999). Therefore, trace and maximum-eigenvalue test statistics are used for panel cointegration testing. Analogously to the time series case, the null hypothesis for both test statistics is that there is no cointegration relationships, against the alternative that there is at most one long-run relation between variables. If null hypothesis is rejected, then alternative is accepted, and the next step is testing the null of having one cointegrating relation against the alternative of having at most two cointegrating relations, and so on.

We also use a more recently panel cointegration test developed by Westerlund (2007). As Persyn and Westerlund (2008) argues, despite of the power gains derived of panel cointegration techniques because of considering the N and T dimensions, many studies do not reject the null hypothesis of no-cointegration, even when a long-run relationship is strongly suggested by economic theory. This testing failure has been interpreted as a loss of power of residual-based cointegration tests, because these procedures requires that coefficients accompanying independent variables in the cointegrating equation to be equal to the short-run coefficients when variables are in differences. Westerlund (2007) developed a panel cointegration test based on assessing whether the error-correction term in a panel error correction model is statistically equal to zero, in which case it is inferred that there is no cointegration. In particular, Westerlund built four tests for testing the null of no-cointegration: two tests evaluate the alternative of having cointegration in the panel as a whole, while the remaining two tests analyze the case in which at least one panel is cointegrated. To see this, we follow Persyn and Westerlund (2007) in considering the error-correction form process:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i (y_{it-1} - \beta_i' x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{it-j} + e_{it} \quad (27)$$

Where y_{it} and x_{it} are non-stationary variables, e_{it} is independent across both i and t , and d_t contains the deterministic components, which will determine if there will be either no constants terms ($d_t = 0$), or there will be only a constant ($d_t = 1$), or there will be a constant with a time trend ($d_t = (1, t)'$). The case in which there is cross-sectional dependence of the error terms, cointegration tests will be robust through considering mean bootstrap methods. As in the Granger Representation theorem, If $\alpha_i < 0$ and statistically significant, then there is error correction when occurs a certain shock, and hence there will be cointegration between y_{it} and x_{it} ; on the contrary, if $\alpha_i = 0$ then there is no error correction and therefore there is no cointegration. In this sense, the null hypothesis is that $H_0 : \alpha_i = 0$ against two sets of alternatives. The first set permits α_i to differ across panels and consists in $H_a^1 : \alpha_i < 0$ for at least one i (Group-mean test). On the other hand, the remaining two tests (panel tests) constrains α_i to be the same across panels, which implies $H_a^2 : \alpha_i = \alpha < 0$ for all i . Westerlund (2007) and Persyn and Westerlund (2008) show that all four test statistics are asymptotically normally distributed the extend to which $T \rightarrow \infty$ and then $N \rightarrow \infty$ sequentially, which in practical terms means that using the test is suitable when T is larger than N . As a practical matter, the two Group-mean statistics are denoted by G_τ and G_α , and the two Panel-test statistics are denoted by P_τ and P_α ⁹. In dealing cross-section dependence in the error-correction residual terms, the cointegration panel test statistics are generalized by using bootstrap methods, which can be found in Westerlund (2007). For robustness of our panel cointegration results, we also use the Westerlund bootstrap approach as an alternative way of testing for panel cointegration.

⁹See Westerlund (2007) and Persyn and Westerlund (2008) for details in constructing Group-mean and panel-test statistics.

3.2.3. Panel cointegration estimation

Assume that the long-run relationship between two variables y_{it} and x_{it} can be represented by the following cointegrating equation:

$$y_{it} = \alpha_i + x'_{it}\beta + \epsilon_{it} \quad (28)$$

Where α_i are panel-specific intercepts capturing fixed-effects, β is a cross-section common vector of long-run coefficients, y_{it} and x_{it} are non-stationary, and u_{it} are stationary disturbance terms, implying that variables in equation (28) are cointegrated. The autorregressive distributive lag (ARDL) process of order (p, q) for y_{it} can be expressed as:

$$y_{it} = \sum_{j=1}^p \lambda_{ij} y_{i,t-j} + \sum_{j=1}^q \delta_{ij} x_{i,t-j} + \mu_i + \epsilon_{it} \quad (29)$$

Where λ_{it} and δ_{ij} are scalars and μ_i is the group-specific effect. Converting equation (29) into its error correction form, we have:

$$\Delta y_{it} = \varphi_i (y_{it} - \alpha_i - x'_{it}\beta) + \sum_{j=1}^p \lambda_{ij}^* y_{i,t-j} + \sum_{j=1}^q \delta_{ij}^* x_{i,t-j} + \epsilon_{it} \quad (30)$$

Where $\varphi_i = -(1 - \sum_{j=1}^p \lambda_{ij})$, $\lambda_{ij}^* = -\sum_{m=j+1}^p \lambda_{im}$ ($j = 1, \dots, p-1$) and $\delta_{ij}^* = -\sum_{m=j+1}^q \delta_{im}$ ($j = 1, \dots, q-1$). In equations (28), (29) and (30) time trends and other kinds of deterministic regressors could be specified. As mentioned in the previous sections, φ_i is the error-correcting term which must be negative and statistically significant for having cointegrated variables.

We will consider five alternative methods for estimating the long-run relationship between our panel time series g_{it} and \tilde{k}_{it} . Following Blackburne and Frank (2007), first we use three methods in estimating long-run coefficients in heterogeneous panels: i) a traditional dynamic fixed-effects (DFE) estimator, ii) a mean-group (MG) estimator (Pesaran and Smith, 1995), and a pool-mean-group (PMG) estimator (Pesaran, Shin and Smith, 1997, 1999). These kind of estimators are correctly used when the panel have both large T and N dimensions, although they have usually been used in a context of $T > N$. In particular, the DFE estimator carries out the estimates of parameters over the pooled sample and restricts the long-run coefficients to be equal through i , although intercepts can differ across groups. Further, the MG approach estimates values for each cross-section intercepts, slope coefficients and error variances, and then makes simple averages of them. After considering the last two opposite properties of DFE and MG estimators, PMG estimator is an intermediate one, in the sense that it permits that intercepts, short-run coefficients and error-variances to vary across groups, but long-run coefficients are constrained to be equal across panels. Since equation (30) is highly non-linear, Pesaran, Shin and Smith (1999) estimate the set of parameters $\{\varphi, \beta, \alpha, \sigma\}$ by the maximum-likelihood approach.

Assesing which estimator is better than the another is an important issue. As Blackburne and Frank (2007) discuss, since the PMG estimator restricts a single long-run coefficient across panels, it gives efficient and consistent estimators when pooling the panels is a true constraint. However, if the pooling restriction is not true, then PMG estimates will be inconsistent, which would make the MG estimator better because it will be consistent in either case. For testing the common-slope restriction, we use the Hausman procedure for testing the difference in both estimators. In this context, the null hypothesis is that the PMG estimator is efficient (in which case this is the preferred approach) against the alternative that the PMG estimator is not consistent, which makes better the MG estimator. Furthermore, DFE estimators can suffer from endogeneity between the error terms

and the lagged dependent variable (Baltagi, Griffin, and Xiong, 2000), which makes necessary testing whether the FE estimator overcomes the MG estimator. To do so, we use again the Hausman test for testing the difference in the two estimators, where the DFE estimator is efficient under the null-hypothesis. If the null is not rejected, then simultaneous equation bias is minimal and DFE estimator would become preferred than the MG estimator (Blackburne and Frank, 2007).

In addition to the maximum-likelihood estimation approach, Ordinary Least Squares (OLS) approach has also been explored in panel cointegration estimation. However, despite of the consistency of OLS estimates in a cointegration single time series approach, Kao and Chiang (2000) show that OLS estimates of long-run coefficients in a panel cointegration framework are inconsistent. Following Baltagi (2013), Phillips and Moon (1999) and Pedroni (1999) proposed a Fully Modified Ordinary Least Squares (FMOLS) estimator and Kao and Chiang (2000) proposed a Dynamic OLS (DOLS) estimator, both approaches dealing with panel cointegration estimation under the assumption of cross-section independence. Kao and Chiang suggested that FMOLS and DOLS estimators are suitable in estimating panel cointegration and demonstrated that both estimators are asymptotically distributed normal. As mentioned in Baltagi (2013), Kao and Chiang studied the finite-sample properties of OLS-type estimators in panel cointegration, and found that although FMOLS improves little the performance of OLS estimates, DOLS seems to behave much better than OLS and FMOLS. Therefore, as an alternative in estimating our cointegrating relation of interest, we also use the FMOLS and DOLS estimators.

4. Results

The aim of this work is to understand why per worker income growth in various developed economies have been stagnated over the past 30 years. Based on the reduced form of the Aguion and Howitt theoretical model, we test for the possibility of a long-run relationship between per worker GDP growth, g_{it} , and the capital stock per efficiency unit of labor, \tilde{k}_{it} , through panel cointegration techniques. In particular, we test for the existence of unit roots in the panel, then we perform the panel cointegration tests, and finally we show the panel cointegration estimates. Further, in section 5 we will interpret the empirical evidence based on the implications of the Aguion and Howitt theoretical model.

4.1. Panel unit root tests

Panel unit root tests results are presented in table 1¹⁰. Since cointegration requires endogenous variables to be equally integrated, capital stock per efficiency unit of labor (in natural logarithms) is differenced to become integrated of order one, because it showed to be integrated of order two in levels. This fact implies that our capital stock per efficiency unit of labor measure in the empirical exercise will be $\Delta\tilde{k}_{it}$, which is denoted ahead as the capital stock per efficient unit of labor growth rate. Table 1 shows that LLC, Breitung and Hadri tests validate the presence of a common unit root in the processes g_{it} and $\Delta\tilde{k}_{it}$, especially when constants (individual effects) and (individual linear) trends are included; whereas IPS and Fisher-type ADF tests reject their null that each panel i has its own unit root.

In particular, LLC and Breitung tests have the null hypothesis that panels contain unit roots against the alternative that all panels are stationary. If the null is not rejected, then the panels, viewed as a whole single set, have a unit root. It can be seen in table 1 that LLC and Breitung tests do not

¹⁰It can be noted along the empirical analysis that results are shown for both periods 1981-2007 and 1981-2009. This cut in the time availability is done for robustness checking of our results. Considering the possibility that our empirical conclusions may be sensitive to the 2008 crisis, we show throughout the empirical analysis that our results are maintained over this cut in the sample.

Table 1: Panel unit root tests

Test	Variable	Deterministics	Type-statistic	Statistic-value (1981-2007)	p-value (1981-2007)	Statistic-value (1981-2009)	p-value (1981-2009)
LLC	g_{it}	no-cons	adjusted-t	-5.8084	0.0000	-4.0782	0.0000
	$\Delta \tilde{k}_{it}$	no-cons		-9.7139	0.0000	-9.4850	0.0000
	g_{it}	cons		-6.5402	0.0000	-4.6075	0.0000
	$\Delta \tilde{k}_{it}$	cons		1.6253	0.9480	0.0584	0.5233
	g_{it}	cons-trend		1.6293	0.9484	3.1405	0.9992
	$\Delta \tilde{k}_{it}$	cons-trend		2.4647	0.9931	4.7704	1.0000
Breitung	g_{it}	cons-trend	t-statistic	1.6485	0.9504	-0.0241	0.4904
	$\Delta \tilde{k}_{it}$	cons-trend		-0.3664	0.3570	2.0450	0.9796
IPS	g_{it}	cons	w-statistic	-8.5084	0.0000	-7.0682	0.0000
	$\Delta \tilde{k}_{it}$	cons		-6.4515	0.0000	-5.6210	0.0000
	g_{it}	cons-trend		-4.3585	0.0000	-2.4591	0.0070
	$\Delta \tilde{k}_{it}$	cons-trend		-2.8764	0.0020	-3.9522	0.0000
Fisher-ADF	g_{it}	no-cons	F Chi-square	70.6717	0.0005	58.3111	0.0107
			Choi Z	-3.2916	0.0005	-2.6219	0.0044
	$\Delta \tilde{k}_{it}$	no-cons	F Chi-square	165.072	0.0000	168.307	0.0000
			Choi Z	-9.3737	0.0000	-9.5743	0.0000
	g_{it}	cons	F Chi-square	149.734	0.0000	145.056	0.0000
			Choi Z	-8.1791	0.0000	-6.7861	0.0000
	$\Delta \tilde{k}_{it}$	cons	F Chi-square	105.850	0.0000	94.6238	0.0000
			Choi Z	-6.5084	0.0000	-5.6159	0.0000
	g_{it}	cons-trend	F Chi-square	86.3926	0.0000	75.9691	0.0001
			Choi Z	-3.8582	0.0001	-1.6892	0.0456
	$\Delta \tilde{k}_{it}$	cons-trend	F Chi-square	56.1146	0.0175	74.5440	0.0002
			Choi Z	-2.2817	0.0113	-3.5673	0.0002
Hadri	g_{it}	cons	Z-statistic	1.4353	0.0756	1.6971	0.0448
			H Z-statistic	0.4396	0.3301	1.0481	0.1473
	$\Delta \tilde{k}_{it}$	cons	Z-statistic	1.5788	0.0572	2.3328	0.0098
			H Z-statistic	2.3982	0.0082	3.6396	0.0001
	g_{it}	cons-trend	Z-statistic	4.2448	0.0000	4.9984	0.0000
			H Z-statistic	4.9170	0.0000	6.5066	0.0000
	$\Delta \tilde{k}_{it}$	cons-trend	Z-statistic	6.3922	0.0000	6.2642	0.0000
			H Z-statistic	5.3817	0.0000	5.8415	0.0000

Source: Authors calculations.

reject the null of unit root for g_{it} and $\Delta \tilde{k}_{it}$ when individual effects and individual linear trends are included, which means that there exist homogeneous unit roots in both variables, once not-observed heterogeneous factors have been controlled for. Further, the Hadri test assesses the null that all panels are stationary against the alternative that at least one panel has a unit root. For g_{it} the Hadri null hypothesis is not rejected when only individual effects are included but not linear trends, and the null is evaluated under the heteroskedastic robust Z-statistic. However, the Hadri tests reject the null of stationarity for variable $\Delta \tilde{k}_{it}$ even when only constants are considered and the null is evaluated under the heteroskedastic robust Z-statistic. Once individual effects and specific linear trends are included together, the Hadri test rejects the null of stationarity for both g_{it} and $\Delta \tilde{k}_{it}$. These results carried out by LLC, Breitung and Hadri tests, support the existence of a common unit root in our variables of interest.

Meanwhile, when non-stationarity is evaluated under the IPS and Fisher-ADF tests, then the null that all individual panels has each one a unit root is rejected in all possible cases, which strengthens the existence of a common unit root over all panel units, rather than an individual unit root for each cross-sectional panel. Therefore, even when IPS and Fisher-ADF tests reject the possibility that each panel has a unit root, LLC, Breitung and Hadri tests conclude that g_{it} and $\Delta \tilde{k}_{it}$ have unit root when they are seen as a whole process, which allows us to go on with the panel cointegration testing exercise.

4.2. Panel cointegration tests

We employ four different panel cointegration tests for g_{it} and $\Delta\tilde{k}_{it}$. Firstly, we test for panel cointegration using the residual-based Pedroni test, which considers the possibility of no-cointegration as the null hypothesis. Table 2 shows the Pedroni test results including individual constants and linear trend terms to control for fixed-effects across panel units. It can be observed that the null hypothesis of no-cointegration is strongly rejected for most of the test statistics, and it is true for both time periods, which implies that g_{it} and $\Delta\tilde{k}_{it}$ are cointegrated.

The last panel cointegration result is verified using the residual-based Kao test and the Fisher-type combined-Johansen test developed by Maddala and Wu (1999). Tables 3 and 4 show respectively the results of these tests. As in the Pedroni test, Kao and Fisher-type tests strongly reject the null hypothesis of no-cointegration between g_{it} and $\Delta\tilde{k}_{it}$ for both time periods, which again support the fact that the per worker output growth rate and the capital per efficiency unit of labor growth rate are panel cointegrated.

Finally, we use the error-correction-based Westerlund test for panel cointegration. Table 5 shows the results, where again the null hypothesis of no-cointegration is strongly rejected for both time periods. No matter which deterministic assumptions are considered, the cointegrating relationship between g_{it} and $\Delta\tilde{k}_{it}$ is again supported. However, Westerlund (2007) warns about the possibility of cross-sectional dependence across the error terms in the error-correction equations. This likely cross-dependency is not considered by the standard Westerlund test, which could alter the cointegration test results suggested by table 5, once the cross-dependence is taken into account. Westerlund (2007) proposed a bootstrapped method for building his panel cointegration test, where the resulting test is robust to the presence of cross-sectional correlation. Results of the Westerlund panel cointegration test robust to cross-sectional dependence are shown in table 6. It can be noted that once the cross-dependence is considered, the panel cointegration results are strongly maintained.

From the above four panel cointegration tests, we can say that results are successful in concluding that g_{it} and $\Delta\tilde{k}_{it}$ are cointegrated, even when cross-sectional dependence across error terms of the error-correction equations is present. Therefore, results support the fact that these two variables have a long-run relationship, as our theoretical framework argues. Under this direction, the next step is estimating the sign and the statistical properties of this long-term link.

4.3. Panel cointegration estimation

Once we know that g_{it} and $\Delta\tilde{k}_{it}$ are cointegrated, we want to estimate the long-run coefficients that relate these two variables. We use five methods in estimating the long-run coefficients of interest. Firstly, we use a maximum-likelihood estimation approach that includes a Pooled-Mean-Group (PMG) estimator, a Mean-Group (MG) estimator, and a Dynamic Fixed-Effects (DFE) estimator¹¹. Second, we focus on an OLS estimation approach, where estimation results of panel DOLS and FMOLS estimators will be shown.

In particular, table 7 shows the estimation results of PMG, MG and DFE estimators, for both 1981-2007 and 1981-2009 time periods. Specifically, it can be noted that the sign of the cointegration coefficients is always negative and statistically significant at 1% level. An implication of the theoretical model is that a negative cointegrated relation between g_{it} and $\Delta\tilde{k}_{it}$ would imply that in the long-run the Shumpeterian curve shifts have dominated over the shifts of the Solowian curve. Further in section 5, we will interpret this results based on the implications of Aguion and Howitt theoretical model.

Table 7 shows that the MG estimator is the greatest one in absolute value, followed by the PMG estimator. As mentioned in section 3.2.3, Blackburne and Frank (2007) discuss that PMG estimator is

¹¹See section 3.2 for a more detailed description of the estimation methods.

Table 2: Pedroni panel cointegration test

Panel cointegration test (Pedroni)	Statistic and p-value (1981-2007)	Statistic and p-value (1981-2009)
Constant		
Panel v	-0.0821 (0.5328)	2.4504 (0.0071)
Panel rho	-10.705 (0.0000)	-8.4558 (0.0000)
Panel pp	-11.584 (0.0000)	-10.856 (0.0000)
Panel-ADF	-10.401 (0.0000)	-11.936 (0.0000)
Weighted Panel v	-0.7819 (0.7829)	-0.3283 (0.6287)
Weighted Panel rho	-11.265 (0.0000)	-8.6208 (0.0000)
Weighted panel pp	-12.272 (0.0000)	-10.904 (0.0000)
Weighted panel ADF	-11.459 (0.0000)	-11.039 (0.0000)
Group rho	-8.4430 (0.0000)	-7.2614 (0.0000)
Group pp	-13.065 (0.0000)	-12.649 (0.0000)
Group ADF	-9.245 (0.0000)	-11.936 (0.0000)
Constant and trend		
Panel v	-3.6934 (0.9999)	-1.6917 (0.9546)
Panel rho	-6.3555 (0.0000)	-4.7709 (0.0000)
Panel pp	-12.617 (0.0000)	-12.185 (0.0000)
Panel-ADF	-11.476 (0.0000)	-12.5922 (0.0000)
Weighted Panel v	-4.2907 (1.0000)	-4.0068 (1.0000)
Weighted Panel rho	-6.7942 (0.0000)	-4.3338 (0.0000)
Weighted panel pp	-13.242 (0.0000)	-11.111 (0.0000)
Weighted panel ADF	-12.556 (0.0000)	-10.545 (0.0000)
Group rho	-4.6012 (0.0000)	-3.4702 (0.0000)
Group pp	-14.155 (0.0000)	-13.234 (0.0000)
Group ADF	-10.413 (0.0000)	-12.092 (0.0000)
Observations	486	522

Source: Authors calculations.

Table 3: Kao panel cointegration test

Panel cointegration test (Kao)	Statistic and p-value (1981-2007)	Statistic and p-value (1981-2009)
ADF	2.4747 (0.0067)	3.0821 (0.0010)
Observations	486	522

Source: Authors calculations.

Table 4: Combined Fisher-ADF panel cointegration test

Panel cointegration test (Combined Johansen)	Fisher trace and p-value (1981-2007)	Fisher max-eigen and p-value (1981-2007)	Fisher trace and p-value (1981-2007)	Fisher max-eigen and p-value (1981-2007)
Constant				
None	88.58 (0.0000)	99.11 (0.0000)	95.42 (0.0000)	102.2 (0.0000)
At most 1	25.31 (0.9085)	25.31 (0.9085)	26.94 (0.8627)	26.94 (0.8627)
Constant-trend				
None	90.21 (0.0000)	96.23 (0.0000)	96.24 (0.0000)	95.45 (0.0000)
At most 1	24.66 (0.9234)	24.66 (0.9234)	31.19 (0.6966)	31.19 (0.6966)
Observations	486		522	

Source: Authors calculations.

Table 5: Westerlund panel cointegration test

Westerlund test	Value (1981-2007)	Z-value (1981-2007)	p-value (1981-2007)	Value (1981-2009)	Z-value (1981-2009)	p-value (1981-2009)
no-constant						
G_{τ}	-1.253	-1.127	0.130	-1.565	-2.399	0.008
G_{α}	-3.336	0.435	0.668	-4.910	-1.034	0.151
P_{τ}	-6.711	-3.894	0.000	-7.235	-4.343	0.000
P_{α}	-6.711	-3.894	0.000	-5.355	-6.343	0.000
constant						
G_{τ}	-3.442	-7.861	0.000	-3.332	-7.340	0.000
G_{α}	-12.425	-4.117	0.000	-14.855	-6.011	0.000
P_{τ}	-13.976	-7.880	0.000	-13.976	-7.880	0.000
P_{α}	-14.513	-9.827	0.000	-16.454	-11.682	0.000
constant-trend						
G_{τ}	-3.730	-7.121	0.000	-3.703	-6.977	0.000
G_{α}	-15.412	-2.122	0.017	-17.666	-3.528	0.000
P_{τ}	-16.053	-8.108	0.000	-15.406	-7.368	0.000
P_{α}	-17.435	-5.883	0.000	-19.791	-7.514	0.000

Source: Authors calculations.

Table 6: Cross-dependence robust Westerlund panel cointegration test

Westerlund robust test	Value (1981-2007)	Z-value (1981-2007)	p-value (1981-2007)	Robust p-value (1981-2007)	Value (1981-2009)	Z-value (1981-2009)	p-value (1981-2009)	Robust p-value (1981-2007)
no-constant								
G_{τ}	-1.457	-1.960	0.025	0.033	-1.624	-2.643	0.004	0.015
G_{α}	-4.181	-0.353	0.362	0.138	-5.138	-1.246	0.106	0.045
P_{τ}	-6.713	-3.895	0.000	0.008	-7.580	-4.638	0.000	0.000
P_{α}	-4.186	-4.631	0.000	0.003	-4.946	-5.744	0.000	0.005
constant								
G_{τ}	-3.076	-6.132	0.000	0.000	-3.233	-6.875	0.000	0.000
G_{α}	-13.255	-4.764	0.000	0.000	-14.682	-5.876	0.000	0.000
P_{τ}	-13.377	-7.278	0.000	0.000	-14.942	-8.851	0.000	0.000
P_{α}	-13.005	-8.386	0.000	0.000	-14.884	-10.182	0.000	0.000
constant-trend								
G_{τ}	-3.468	-5.752	0.000	0.000	-3.478	-5.802	0.000	0.000
G_{α}	-15.815	-2.373	0.009	0.000	-16.318	-2.687	0.004	0.000
P_{τ}	-16.053	-8.108	0.000	0.000	-16.446	-8.557	0.000	0.000
P_{α}	-17.435	-5.883	0.000	0.000	-17.380	-5.845	0.000	0.000

Source: Authors calculations.

an intermediate between MG and DFE estimators, in the sense that it permits that intercepts, short-run coefficients and error-variances to vary across groups, but long-run coefficients are constrained to be equal across panels. Since the PMG estimator restricts a single long-run coefficient across panels, it gives efficient and consistent estimators when pooling the panels is a true constraint. However, if the pooling restriction is not true, then PMG estimates will be inconsistent, which would make the MG estimator better. Although the panel cointegration tests rejected the null of no-cointegration both at the within (panel-specific) and between (Group-common) dimensions, testing the common-slope restriction is mostly motivated by the panel unit root results, which indicated that there exists a common unit root in both g_{it} and $\Delta\tilde{k}_{it}$ once individual effects are controlled for (LLC, Fisher-ADF and Hadri) instead of a situation in which each panel has a unit root. For testing whether the common-slope is true, we use the Hausman procedure for testing the difference in both estimators. In this context, the null hypothesis is that the PMG estimator is efficient (in which case this is the preferred approach) against the alternative that the PMG estimator is not consistent, which makes better the MG estimator. Further, since the DFE estimator only permits that intercepts can vary over the panel units (considering common short-run coefficients, common error variances and common long-run coefficients), we also test the null that the DFE estimator overcomes the MG estimator.

Hausman test results are shown in table 8. It can be noted that PMG estimates are preferred over the MG estimates (null is not rejected), but MG estimates are preferred over DFE estimates (rejection of the null hypothesis at 10% significance level). This results makes the PMG estimates preferred over MG and DFE estimates, which is consistent with the panel unit root tests results. These findings together mean that the restriction of a common long-run coefficient is true, and that the PMG estimator is a good approach in estimating our long-run relationship of interest.

We also estimate the long-run coefficient between g_{it} and $\Delta\tilde{k}_{it}$ through the OLS estimation approach. Given that OLS estimates suffer of endogeneity between the error term and the lagged dependent variable, we instead carry out the estimates by FMOLS and DOLS. However, Kao and Chiang studied the finite-sample properties of OLS-type estimators in panel cointegration, and found that although FMOLS improves little the performance of OLS estimates, DOLS seem to behave much better than OLS and FMOLS (Baltagi, 2013). Estimates of the long-run coefficient by FMOLS and DOLS are shown in table 9. There are three ways of estimating by FMOLS and DOLS, so that i) the whole coefficient may be either an average of cross-section standard FMOLS and DOLS estimates (Group-mean), or ii) it may be the result of weighting the data by the panel-specific long-run error-variances and then estimate the pooled sample by FMOLS and DOLS (Pool-weighted), or iii) it may be the result of performing standard FMOLS and DOLS over the pooled sample, once deterministic components have been dropped from g_{it} and $\Delta\tilde{k}_{it}$. It can be observed that all long-run coefficients in table 9 are negative and statistically significant, almost all at 1% significance level.

Given that the common-slope assumption is true (by the Hausman test and panel unit root tests) and that Kao and Chiang (2000) argue that DOLS tend to behave better than FMOLS, it seems reasonable that pooled and pool-weighted DOLS estimates are the preferred estimates in table 9, as these estimation ways considerably control for heterogeneity across panels, maintaining the common-slope restriction. It can be noted that these estimates have the highest goodness of fit numbers (R^2) in table 9, and the coefficient values are close to the PMG ones. If we take the PMG and DOLS estimators as our preferred ones, then controlling for fixed effects a long-run equilibrium increase of $\Delta\tilde{k}_{it}$ in 1 percentage point would have made decrease g_{it} between 0.0720 and 0.1178 percentage points if the sample goes until 2007, but between 0.0978 and 0.1536 percentage points if the sample goes until 2009. From a goodness of fit perspective (R^2), since the error terms of PMG and DOLS estimates are stationary and the not-observed heterogeneity seems to be important, the fixed effects play a really important role (unexplained by our paper) and the long-run fluctuations of g_{it} not explained by the long-run fluctuations in $\Delta\tilde{k}_{it}$ remain still high.

Table 7: PMG, MG and DFE panel cointegration estimates

Estimator	Coefficient and p-value (1981-2007)	Coefficient and p-value (1981-2009)
PMG	-0.0720 (0.000)	-0.0978 (0.000)
MG	-0.1218 (0.001)	-0.1693 (0.003)
DFE	-0.0605 (0.009)	-0.0898 (0.000)
Obs.	468	504

Source: Authors calculations.

Table 8: Hausman tests for differences between PMG, MG and DFE estimates

Hausman Test	Statistic (p-value) (1981-2007)	Statistic (p-value) (1981-2009)
MG vs PMG	2.28 (0.131)	2.00 (0.157)
MG vs DFE	5.00 (0.025)	3.04 (0.081)

Source: Authors calculations.

Table 9: DOLS and FMOLS panel cointegration estimates

DOLS and FMOLS	DOLS (1981-2007)	DOLS (1981-2009)	FMOLS (1981-2007)	FMOLS (1981-2009)
	Coefficient (p-value) (Obs.) (R ²)	Coefficient (p-value) (Obs.) (R ²)	Coefficient (p-value) (Obs.) (R ²)	Coefficient (p-value) (Obs.) (R ²)
Group-mean				
Constant	-0.1343 (0.0000) (451)	-0.1601 (0.0000) (478)	-0.0976 (0.0000) (468)	-0.1344 (0.0000) (504)
	(0.2918)	(0.2460)	(0.1922)	(0.1672)
Constant-trend	-0.0708 (0.0203) (454)	-0.1124 (0.0002) (477)	-0.0829 (0.0001) (468)	-0.1164 (0.0000) (504)
	(0.2565)	(0.1812)	(0.2146)	(0.1936)
Pool-weighted				
Constant	-0.1178 (0.0000) (451)	-0.1496 (0.0000) (478)	-0.1249 (0.0039) (468)	-0.2010 (0.0000) (504)
	(0.3378)	(0.2877)	(0.1857)	(0.1153)
Constant-trend	-0.1162 (0.0000) (454)	-0.1536 (0.0000) (477)	-0.1297 (0.0073) (468)	-0.2249 (0.0000) (504)
	(0.3786)	(0.3318)	(0.2315)	(0.1499)
Pooled				
Constant	-0.1045 (0.0002) (451)	-0.1267 (0.0000) (478)	-0.0816 (0.0000) (468)	-0.1091 (0.0000) (504)
	(0.3382)	(0.2891)	(0.2001)	(0.1840)
Constant-trend	-0.0790 (0.0064) (454)	-0.1257 (0.0000) (477)	-0.0885 (0.0000) (468)	-0.1175 (0.0000) (504)
	(0.3812)	(0.3334)	(0.2436)	(0.2332)

Source: Authors calculations.

4.4. Econometric evidence

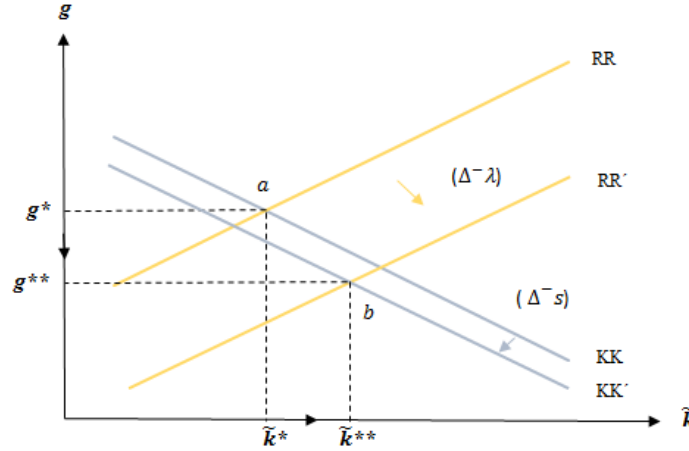
Summarizing the econometric results, the most important findings are the following:

- Even when IPS and Fisher-ADF tests reject the possibility that each panel has a unit root, LLC, Breitung and Hadri tests support the existence of a common unit root in g_{it} and $\Delta\tilde{k}_{it}$, which means that they have a unit root when they are seen as a whole process.
- g_{it} and $\Delta\tilde{k}_{it}$ are cointegrated, even when there is cross-sectional dependence across error terms in error-correction equations.
- If we take the PMG and DOLS estimators as our preferred ones, then, controlling for fixed effects, a long-run equilibrium increase of $\Delta\tilde{k}_{it}$ in 1 percentage point, would have made decrease g_{it} between 0.0720 and 0.1178 percentage points if the sample goes until 2007, but between 0.0978 and 0.1536 percentage points if the sample goes until 2009.

From the findings above, we can conclude that g_{it} and $\Delta\tilde{k}_{it}$ have common unit roots, they are cointegrated, and are negatively related in the long-run.

5. Discussion and conclusions

Figure 3: Shifts in Schumpeterian (RR) and Solowian (KK) curves



The econometric exercise consisted in estimating a long-run relationship between per worker growth rates and capital stock per efficiency unit of labor growth rates, which drove us to an estimation of a panel cointegrating equation between g_{it} and $\Delta\tilde{k}_{it}$, once we concluded that these variables were non-stationary. We decided to include only endogenous variables and excluded from the cointegrating relation variables such as λ , s , n and δ because the theoretical model of Aguión and Howitt consider these last variables as exogenous. Therefore, since g_{it} and $\Delta\tilde{k}_{it}$ proved each to have a common unit root, the sign of the cointegration between these two variables allows us to infer the extent to which each exogenous variable is affecting the long-run equilibrium $\{g_{it}, \Delta\tilde{k}_{it}\}$, according to the Aguión and Howitt model.

The fact that g_{it} and $\Delta\tilde{k}_{it}$ have common unit roots and are cointegrated, indicates that their relationship is stable through time, but also that they are continuously responding to permanent exogenous shocks. As it is predicted by the theoretical model, exogenous movements in λ would make g_{it} and $\Delta\tilde{k}_{it}$ to relate negatively in the long run, whereas exogenous shocks to s , n and δ would make g_{it} and $\Delta\tilde{k}_{it}$ to relate positively in the long-term. Therefore, the sing of the net equilibrium relationship between g_{it} and $\Delta\tilde{k}_{it}$ through time will determine which exogenous shocks domain over the long-term movements in the $\{g_{it}, \Delta\tilde{k}_{it}\}$ equilibrium. Given that the panel cointegration estimates indicate that this relationship is negative and statistically significant throughout several methods, it can be inferred from the theoretical model that efficiency of R&D investments effects on the $\{g_{it}, \Delta\tilde{k}_{it}\}$ equilibrium domain over the solownian exogenous factors, such as s , n and δ . In graphical terms, according to figure 2 this means that the RR curve has been shifting in greater magnitudes than the KK curve has shifted over time.

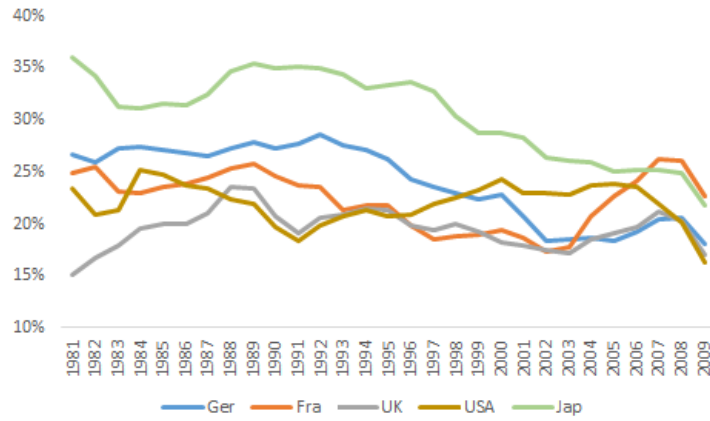
Figures 4, 5 and 6 show respectively Penn World Tables data of the investment rates, population growth rates and capital stock depreciation rates for five big countries included in the sample. They show that investment rates have a clearly negative trend through time, not all population growth rates are decreasing, and depreciation rates seem to be roughly stable. Keeping in mind the theoretical effects of these exogenous variables on the long-run equilibrium of g_{it} and $\Delta\tilde{k}_{it}$, the up-right shift of the KK curve derived from a whole-brief decrease in population growth rates is more than compensated by a down-left shift of the KK curve derived from a clearly declining path in investment rates. Therefore, we interpret the joint movements in s , n and δ as a contraction of the KK curve led by a declining path in investment rates.

However, since the panel cointegration results revealed a negative long-run relationship between g_{it} and $\Delta\tilde{k}_{it}$, the inwards Solownian curve shift due to the falling investment rates, has contributed to the slowdown in per worker output growth rates but our empirical results and our data imply that declining investment rates are not the principal explanation for declining per worker growth. Figure 7 shows that capital stock per efficiency unit of labor has an increasing trend during our sample period. Since the theoretical model predicts that a contraction of the KK curve (motivated by a decrease in investment rates) results in lower per worker output growth accompanied by less capital per efficiency unit of labor, investment rates are not the key explanation for the slowdown in per worker output growth. In contrast, as we have seen that per worker product growth is declining and capital per efficiency unit of labor grows over time, the theoretical model of Aguión and Howitt implication is that this endogenous situation is mainly explained by an exogenous decrease in the efficiency of R&D investments. At this respect, figure 3 shows the new equilibrium from situation a to situation b , in which the economy is in its steady-state equilibrium (a) and then it shifts to a situation (b) characterized by lower long-run per worker output growth with a greater capital stock per efficiency unit of labor.

How to understand a situation in which investment rates falls and capital per efficiency unit of labor grows? The reason implied by the theoretical model is that labor-augmenting technological progress is endogenously falling over time, which is motivated mostly by an exogenous deterioration of the environment conditions for the transformation of capital investment in new technology. This result means that marginal productivity of capital stock for making innovations has decreased, which makes less profitable expenses in R&D. Declining investment rates and decreasing efficiency of R&D investments explaining low growth rates, are consistent with various findings in the literature. For instance, Desroches and Francis (2006) and Eichengreen (2015) argue that the slowdown in productivity growth has been related to a decrease in real interest rates since 1980s, which can be explained by an excess of desired savings over desired investments (Fisher, 2006; IMF, 2014; Eichengreen, 2015). Furthermore, Eichengreen (2015) point that low real interest rates and the slow economic growth could be associated to a dearth in attractive investment opportunities. For instance, Gordon (2012) argues that returns to innovation processes have slowed since 1970s.

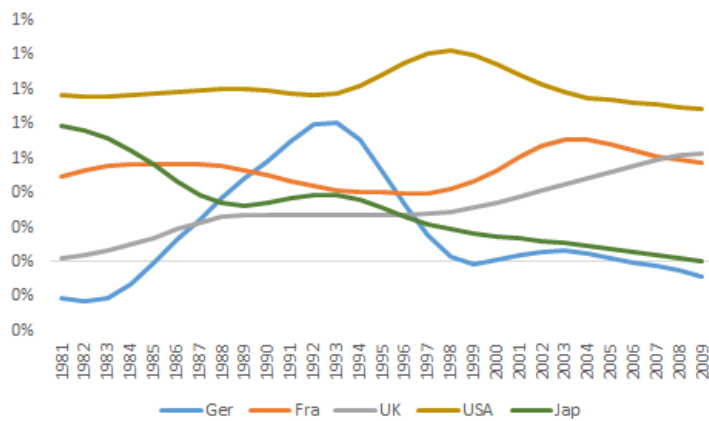
Since we conclude that a decrease in the efficiency of R&D expenditures is the key explanation for

Figure 4: Investment rates



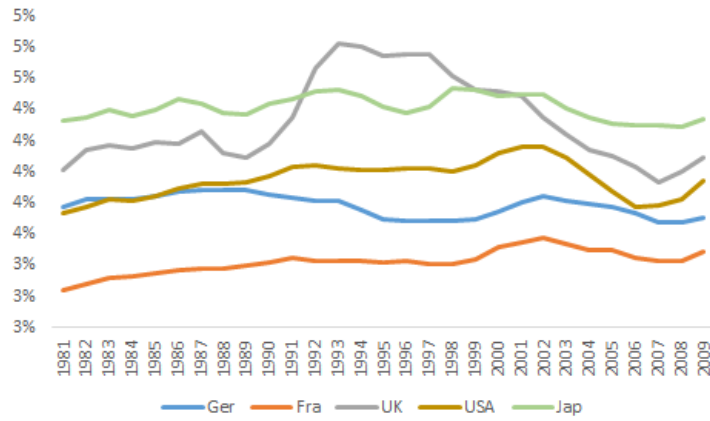
Source: Penn World Tables version 8.1.

Figure 5: Population growth rates



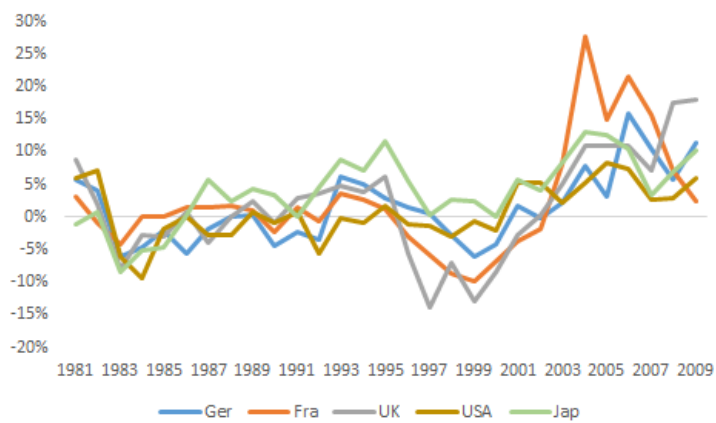
Source: Penn World Tables version 8.1 and authors calculations.

Figure 6: Depreciation rates



Source: Penn World Tables version 8.1.

Figure 7: Capital stock per efficiency unit of labor growth rates



Source: Penn World Tables version 8.1 and authors calculations.

declining per worker output growth rates, one implication is that economic policies must be focused in generating a suitable environment for investment and R&D expenditures to be transformed in new technology. Monetary and fiscal policy stimuli have demonstrated recently (in Japan, USA, and several European countries) their serious difficulties in recovering previous per worker product growth numbers. Inasmuch as technological progress has had a decreasing pattern, and capital stock per efficiency unit of labor growth rate has exhibited the opposite, then effects of such stimuli will contribute to a greater “excess” of capital stock per efficient unit of labor. Improving conditions under which investment and R&D expenditures generate new technology would be a factor for a stronger productivity growth. In particular, IMF (2015) found that the key reason for the negative trend in TFP growth in advanced economies has been the existence of policy rigidities that are hurdles to an efficient allocation of capital and labor inputs between and within sectors (Hopenhayn and Rogerson, 1993; Lagos, 2006; Foster, Haltiwanger, and Syverson, 2008; IMF, 2015). Focusing economic policy on a reduction in such rigidities could probably lead to a suitable environment for investment and R&D expenditures to be transformed in new and better technologies.

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